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MULTI-OBJECTIVE DESIGN FOR A NEW TYPE OF FRAME SAW MACHINE

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ABSTRACT

A new type of frame saw machine with four-bar parallelogram linkage mechanism has been recently studied around the world. In this paper, an advanced model including 8 control parameters, 9 functional constraints and 9 objective functions was developed with a goal to interact and deal with inconsistencies among four stages within design process of this machine, such as concept, analysis, technology and multi-criteria decision-making processes. The last stage or the most important one was in fact a multi-objective optimization problem; in order to tackle with it the authors used a visual interactive analysis method (VIAM) with an application of single-objective optimization techniques. By using VIAM for three manufacturing scenarios, 28 Pareto optimal solutions have been determined; hence the designer is able to make a proper decision at every scenario.

KEYWORDS: Decision Support Systems, Decision Processes, Multi-Objective Optimization, Visual Interactive Analysis Method & Frame Saw Machine

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Original Article

INTRODUCTION

A new type of frame saw machine with four-bar parallelogram linkage mechanism has been recently studied and developed [1-3]; an illustration of which is shown in Figure 1. Unlike traditional frame saw machine, it was designed to ensure dynamic self-balancing system; consequently, it can work steadily at high speed (approximately 3000 rpm) without consideration of an extra balancing mechanism. The movement is transmitted from the leading shaft (lower) to the shaft being led (upper) directly by mean of the saw blade without using any other drive system. The operational principle and structural improvements have significantly reduced the sawblade length in comparison with that of the equivalent traditional frame saw machine, thus stiffness and stability of the sawblade have been enhanced considerably.

However, a task to solve inconsistency issues arisen within a new type of frame saw machine design process seems to be a complex multi-objective model. If the current multi-objective optimization methods are applied to deal with this, it might make the task becoming out of its essence. The reason is that, most of these methods implement the idea of converting the criteria into an equivalent function (or scalar methods) by using many techniques such as weighted minimax (maximin), compromise programming, weighted sum, bounded objective function, modified Tchebycheff, weighted product, exponential weighted sum, etc. [4-8]. Generally considering, the equivalent function of all criteria or objective functions is as

follows: $\Psi(\boldsymbol{\alpha}) = convolution\{\Phi_1(\boldsymbol{\alpha}), \Phi_2(\boldsymbol{\alpha}), \ldots, \Phi_M(\boldsymbol{\alpha})\}$, where $\boldsymbol{\alpha} = (\alpha_1, \alpha_1, \ldots, \alpha_N)$ – a vector of N parameters, Φ_i – an objective function i (i = 1.. M). Afterward, it needs to find the extreme of the equivalent function; in order to do that, several current single-objective optimization algorithms can frequently be used [9-14], such as numerical direct methods or modern methods with behavioral characteristic-based approach to biological and molecular systems, swarm of insects, neural network etc. These algorithms yield optimization values with insignificant error. Nevertheless, by using the minimum of the resultant equivalent function, the outcome of any objective function from one algorithm is different from the one of the same function from another algorithm. In other words for example, the minimum of the resultant equivalent function yielded from the algorithms are more or less equal, as assigned $\Psi^{\oplus}_{method1} \approx \Psi^{\oplus}_{method2} \approx \ldots \Psi^{\oplus}_{methodK}$ respectively; while applied conversely, the results of every single-objective function from every algorithm are rarely alike, or $(\Phi_i)^{\oplus}_{method1} \neq (\Phi_i)^{\oplus}_{method2} \neq \ldots \neq (\Phi_i)^{\oplus}_{methodK}$ $(i = 1.. M)$.

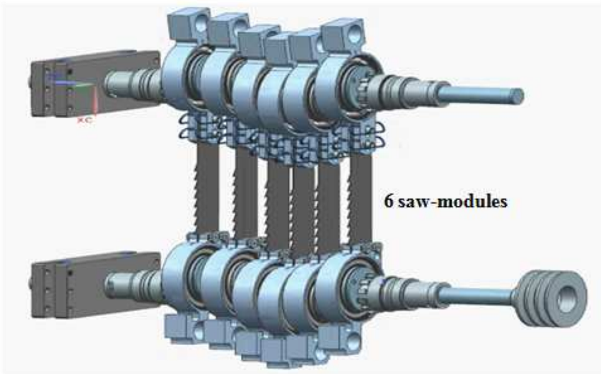


Figure 1: A New Type of Frame Saw Machine with 6 Saw-Modules

Nonetheless, it is concerned that whether the results of every single-objective function are in coincidence with the requirements within the design process, its importance grade might be varied at a specific manufacturing circumstance. Besides, non-scalar optimization methods have been lately used, Brito and his co-workers [15] considered a relaxed projection method, which coordinates a reflection technique to obtain a feasible point with projected sub-gradient method; while in other study [16] the multi-objective optimization methodology based on harmony search and Pareto front approaches was proposed to design energy-efficient shading devices; and there are also other methods such as lexicographic, goal programming, physical programming, genetic, nash arbitration, described elsewhere in Ref. [17-18], and/or multi-objective genetic algorithm [0], Gaussian process regression [20], Nash/Adjoint optimization methods [22].

Nevertheless, most of the aforementioned methods did not concentrate on arranging an interactive panel, which allows the designer to be aware of feasible criteria. This leads to the fact that there is no basis to evaluate and analyze the resultant optimal solutions. Yet, these methods are only capable of finding out solutions in one-way direction; it means that although the resultant solution from every algorithm is Pareto solution, it might not satisfy the designer. For example, there is a case that one objective function yields a very good result, while another function has not yielded a desirable result yet. This shows that there is no professional interaction or control from the designer during solution search, that the obtained solution is barely the result from a fixed algorithm and no more beyond that. Moreover, these methods often tend to improve the efficiency of Pareto solution search (less search time, less amount of test points). It is noted that the most important thing is that the obtained solution needs to meet the technical requirements; and when they are varied, it must be

flexible to obtain a satisfactory solution correspondingly. Therefore, in order to deal with the complex multi-objective model within design process for a new type of frame saw machine, the authors propose a visual interactive analysis method or VIAM based on a single-objective optimization techniques.

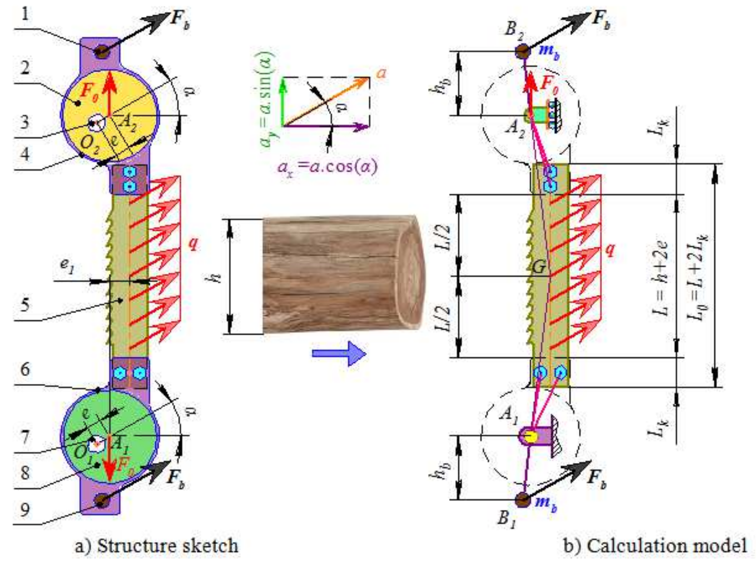
PROBLEM STATEMENT

The main structure of the frame saw machine consists of similar sawblade modules, as shown in Figure 2. The sawblade module is installed on lower- and upper shafts, and moved by four-bar parallelogram linkage mechanism. There is a key connection between the shaft and the eccentric disc. Besides, the eccentric disc is joined with the housing part by hinge connection. The rotational movement of the upper shaft is yielded from the lower shaft with rotation speed n (revolution per minute) through the sawblade modules themselves. The matter-spot on saw-module moves with eccentricity of circular motion, e, at the same velocity and acceleration [23]. Centrifugal acceleration of the matter-spot on saw-module has a constant magnitude such as $a=e*(2\pi/60)^2$, but its direction changes continuously. During no-load operation, the sawblade is subjected to initial tensile force F_0 with eccentricity e_1, inertial uniformly distributed force q along blade length, and moment generated by the inertial force F_b of counterbalance. Lower – and upper housing parts are designed to ensure that their gravity centers coincide with the center of eccentric disc (A_1, A_2), thus they do not cause inertial moment acting on the sawblade. The entire moment of inertia effects on the blade with a maximum magnitude at the location, where the centrifugal acceleration is in the horizontal direction, i. e. the position with rotational angle $\alpha = 0^o$ or 180^o. Assumed that the machine needs to be designed to be able to saw logs with the largest radius h, the minimum free length of blade and the total blade length would be $L = h + 2e$ and $L_0 = L + 2L_k$ respectively, where L_k is the partial blade length, which is clamped at each end and is considered as a constant in the calculation model.

The set of control parameters, which decides criteria of saw machine, includes: eccentricity of the circular motion e and shaft rotation speed n, blade dimension, counterbalance mass m_b and distance h_b, the magnitude of initial tensile force F_0 and eccentricity of saw blade tension e_1, as described in Table 1. Besides, the functional constraints and quality criteria or objective functions are presented in Table 2 and Table 3 respectively [24].

Table 1: Control Parameters

Parameters -Symbols in Model	Original Symbol	Initial Minimum Permissible Value	Initial Maximum Permissible Value	Units	Definition
α_1	E	0.03	0.035	m	Eccentricity of the circular motion
α_2	b	0.06	0.1	m	Saw blade width
α_3	t	0.001	0.002	m	Saw blade thick-ness
α_4	e_1	0	0.08	m	Eccentricity of saw blade tension
α_5	h_b	0.1	0.2	m	Distance h_b
α_6	m_b	0	1	kg	Counterbalance mass
α_7	F_0	500	2000	N	Tension force magnitude
α_8	n	2000	3000	rev./min.	Shaft rotation speed



1, 9 – Counterbalance; 2 – Upper Eccentric; 3 – Upper Shaft; 4 – Upper Housing part; 5 – Saw Blade; 6 – Lower Housing Part; 7 – lower Shaft; 8 – Lower Eccentric

Figure 2: Saw Blade Module in a New Type of Frame Saw Machine

Table 2: Functional Constraints

Symbol	Requirement	Explanation
f_1	≤ 0	Requirement for an absence of resonance
f_2	≥ 0	Stability requirement of sawblade under inertial forces
f_3	≤ 0	Balance state of the saw-module
f_4	≥ 0	Tensile force requirement
f_5	≥ 0	Strength requirement of sawblade
f_6	≥ 0	Fatigue requirement of sawblade
f_7	≥ 0	Initial rigidity requirement of sawblade
f_8	≥ 0	Stability requirement of sawing processes
f_9	≥ 0	Specified requirement (real value exists) for criteria Φ3

The mathematical model herein includes 8 control parameters (Table 1), 9 functional constraints (Table 2) and 9 objective functions (Table 3). It is necessary to find solutions satisfying with the constraints and the functions need to be optimized in compliance with the technical requirements of the saw machine.

Table 3: Objective Functions

Symbol	The Direction of Improvement	Explanation
Φ_1	MIN	Total mass of the sawblade and the counterbalances
Φ_2	MIN	Overall dimension
Φ_3	MAX	First natural frequency of the saw-module
Φ_4	MAX	Critical speed of shaft rotation
Φ_5	MIN	Tension force magnitude
Φ_6	MAX	Operating speed of shaft rotation
Φ_7	MAX	Stability of sawing processes
Φ_8	MAX	Initial rigidity of unstrained sawblade (in the absence of sawing force)
Φ_9	MIN	Sawblade thickness

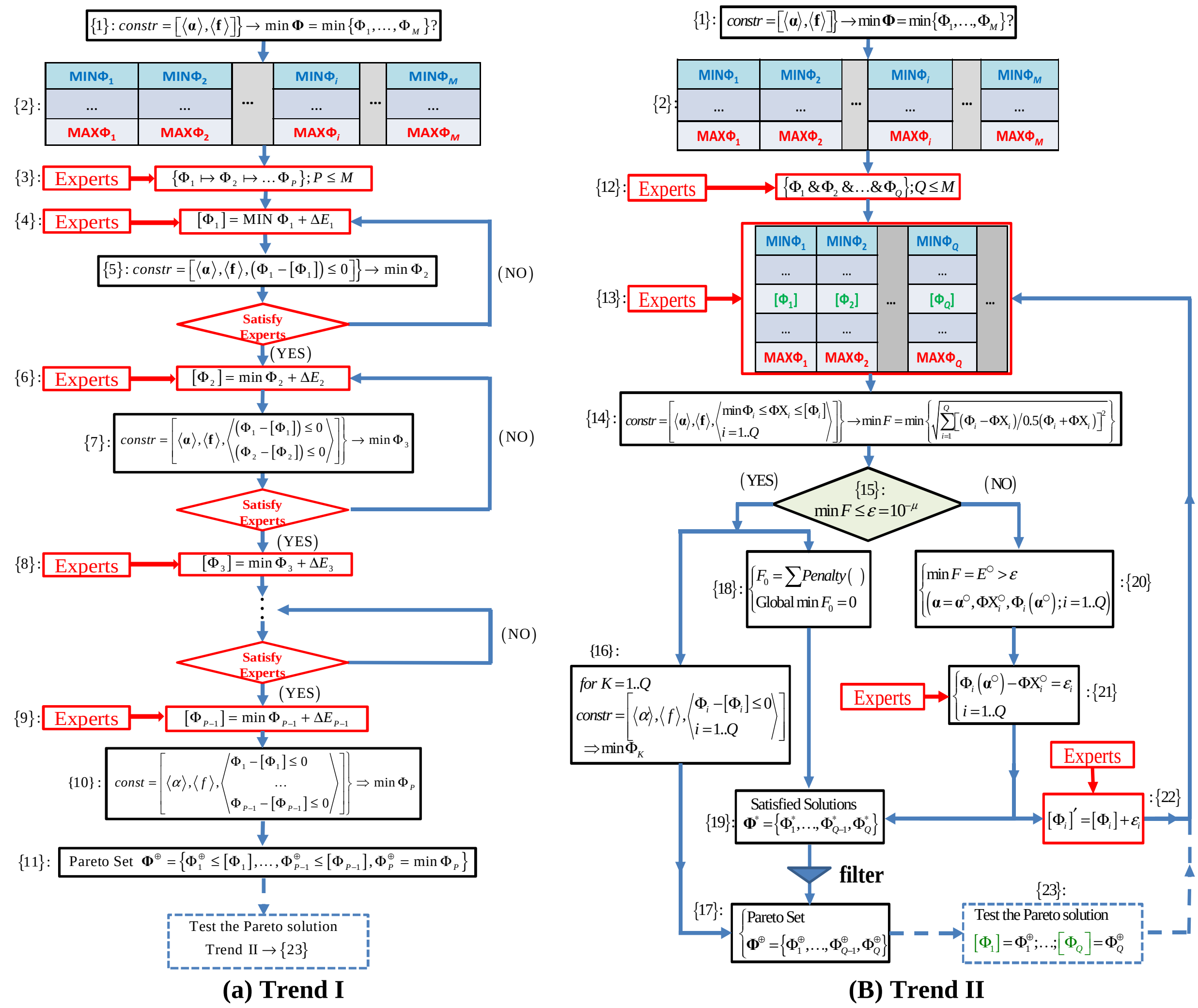


Figure 3: Algorithm of VIAM

METHOD AND ALGORITHM OF SOLUTION

The main idea of VIAM is to use the single-objective optimization techniques as a tool, with the aim of finding suitable solution for multi-objective model, satisfying designer requirements. The detailed steps in solution search and generalized diagram are described in Figure 3a and 3b, respectively.

Function Value and Interactive Panel

The model {1} is the first step, as shown in Figure 3a, hence it is necessary to optimize the vector $\mathbf{\Phi}$ of M objective functions with the parameter vector $\langle\boldsymbol{\alpha}\rangle$, as well as the functional constraints $\langle\mathbf{f}\rangle$ (where, $\boldsymbol{\alpha} = \{\alpha_1, \alpha_2,\ldots, \alpha_N\}$, $\mathbf{f} = \mathbf{f}(\boldsymbol{\alpha}) = \{ f_1(\boldsymbol{\alpha}), f_2(\boldsymbol{\alpha}),\ldots, f_K(\boldsymbol{\alpha})\}$, $\mathbf{\Phi} = \mathbf{\Phi}(\alpha) = \{ \Phi_1(\boldsymbol{\alpha}), \Phi_2(\boldsymbol{\alpha}),\ldots, \Phi_M(\boldsymbol{\alpha})\}$). The condition of parameter $\boldsymbol{\alpha}$ is as follows: $a_i \le \alpha_i \le b_i$; $a_j \le \alpha_j$ or $\alpha_k \le b_k$ (i, j, k ϵ [1; N]). Besides, the condition of functional constraints $\mathbf{f}$ is as follows: $f_l(\boldsymbol{\alpha}) \le 0$; $f_m(\boldsymbol{\alpha}) = 0$; $f_n(\boldsymbol{\alpha}) < 0$ or $f_o(\boldsymbol{\alpha}) \neq 0$ (l, m, n, o ϵ [1; K]). Next step {2} is to use up-to-date single-objective optimization algorithms [4-9, 12, 13], with the aim to determine minimum and maximum values or MINΦ_i and MAXΦ_i, respectively, of an objective function (taking into account the relationship), and include these values into a table. This is an interactive panel, which helps engineers significantly to analyses and makes a decision during solution search. When the final solution is a

vector $\mathbf{\Phi}^{\oplus}=\{\Phi_1^{\oplus},\Phi_2^{\oplus},\ldots,\Phi_M^{\oplus}\}$ with values satisfying designer' requirements, i. e. $\Phi_i^{\oplus}\in[\mathrm{MIN}\Phi_i;\mathrm{MAX}\Phi_i]$, there are two principal trends in solution search of multi-objective optimization problem.

- Trend I (Figure 3a): Based on the table in the step {2}, the designer defines a "strict" priority procedure for criteria, for instance in {3}: (the rest criteria (M – P) are not considered, because their importance grades do not reach to a vigilant level). It means that the function 1 is the most important one, it needs to be the most optimal value, then the function 2 also has to reach the most optimal value after making concessions on importance to the function 1, and the process carries on for other subsequent criteria.
- Trend II (Figure 3b) is equalizing classification, i. e. there is a group of first priority functions, which have a similar importance, such as {12}: Dealing with an optimization of one function in this group might aggravate the results of other functions, thus in this circumstance the analysis and discussion among designers need to be carried out.

It is important to indicate that the Trend II is a generalized case; it can be converted into the Trend I, when Q = 1 occurs gradually M times, or extend to all of functions as $Q = M$. However, in many cases though Trend II is used to solve the problem, but when it is necessary to make a decision, sometimes randomly it is prone to Trend I, because it is rarely capable of optimizing two or more functions simultaneously, consequently there needs to be a "reluctant" agreement to make a priority for any individual function.

Block "Approach by Priority Order of the Criteria"

This approach to finding the solution by Trend I (Figure 3a) is as follows. First, it needs to optimize the most important function 1 (step {4}). Hence, the optimal value of function 1 or MINΦ_1 can be used for further steps. However, while setting a goal for Φ_1 is such high, the obtained solution of other functions might be undesirable. Therefore, the designer needs to extend the requirement for Φ_1, and set its value within a threshold $[\Phi_1]=\mathrm{MIN}\Phi_1+\Delta E_1$ (with the deviation $\Delta E_1>0$). If so, among the obtained solutions that $\Phi_1\le[\Phi_1]$, there might be the most favorable option for the function Φ_2. While searching the optimal value for the function Φ_2 or $\min\Phi_2$, it needs to add the constraint $\Phi_1-[\Phi_1]\le 0$ (an absolute form) or $\left[(\Phi_1-[\Phi_1])/\left|0.5\cdot(\Phi_1+[\Phi_1])\right|\right]\le 0$ (a relative form) {5}. As soon as at this step, the function 2 is optimized with consideration of the constraints of the function 1, thus the obtained value $\min\Phi_2$ is often greater than the $\mathrm{MIN}\Phi_2$ in the interactive panel {2}. Then, the value $\min\Phi_2$ needs to be verified by the experts, because there might be a situation that this value is inferior and inacceptable. If so, the threshold $[\Phi_1]$ needs to be extended more with the aim to re-solve the step {5}. While, in the case that the obtained value minΦ_2 complies with the requirements, similarly they set a threshold $[\Phi_2]=\min\Phi_2+\Delta E_2$ for the function 2 (with the deviation $\Delta E_2>0$) with the goal to find solutions for optimizing the succeeding functions (step {6}). While searching the optimal value for the function 3 or $\min\Phi_3$, it needs to add two constraints $\begin{cases}(\Phi_1-[\Phi_1]\le 0)\\(\Phi_2-[\Phi_2]\le 0)\end{cases}$ or $\begin{cases}\left[(\Phi_1-[\Phi_1])/\left|0.5\cdot(\Phi_1+[\Phi_1])\right|\right]\le 0\\\left[(\Phi_2-[\Phi_2])/\left|0.5\cdot(\Phi_2+[\Phi_2])\right|\right]\le 0\end{cases}$ (step {7}).

By the same manner, the designer sets a threshold $[\Phi_3] = \min\Phi_3 + \Delta E_3$ for this function (step {8}) etc., and so on there are a series of thresholds $[\Phi_1],[\Phi_2],...,[\Phi_{P-1}]$ for the first (*P*-1) functions (step {9}). Based on (*P*-1) constraints of the corresponding threshold and necessity of minimizing P^{th} function, eventually the solution with a desirable priority order can be achieved (step {10}). The obtained result $\mathbf{\Phi}^{\oplus} = \{\Phi_1^{\oplus},\Phi_2^{\oplus},\dots,\Phi_P^{\oplus}\}$ is just a Pareto solution ({11}), which means that there is no better solution for all functions simultaneously. In case, the designer needs to verify exactly whether the obtained solution is Pareto one, it is possible to shift to Trend II at step {23}, which will be described with more details in section 3.3.

<u>*Note*</u>: When dealing with the problem by this approach, the most important issue is a next question. Although an individual function might reach an optimal value, whether or not this value is desirable, while extending slightly the threshold, it helps to acquire more optimal solutions for other criteria? This cannot be predicted by an engineer; therefore it is necessary to have a tool to control the threshold $[\Phi_i] = \min\Phi_i + \Delta E_i$, so that it is capable of extending constraint condition of subsequent functions relevantly and precisely. Thus, it is able to obtain suitable solutions for other functions.

Block "Approach by Equalizing Classification of the Criteria"

Trend II (Figure 3b) suggests that there is a group of *Q* functions with the same importance, whereas the rest functions are random (step {12}). The experts herein need to set a "threshold" value of $[\Phi_i]$ for the function *i* in the interactive panel {13}. Range of satisfied solutions will be a set of vectors $\mathbf{\Phi X} = \{\Phi X_1,\Phi X_2,\dots,\Phi X_Q\}$, where the final value ΦX_i of the function needs to comply with the condition $\Phi X_i \in \left[\min\Phi_i;[\Phi_i]\right]$. The main idea is to find that vector **ΦX**. This approach presents as follows; firstly considering the aforementioned condition as the constraints {14}, hence it is necessary to find not only *N* parameters x_j (j = 1.. *N*), but also *Q* final value of the function ΦX_i (i = 1.. *Q*) while minimizing the equivalent error function

F: $\min F = \left[\begin{array}{l} \min\left\{\sum_{i=1}^{Q}\left|(\Phi_i - \Phi X_i)/0.5(\Phi_i + \Phi X_i)\right|\right\} \\ \min\left\{\sqrt{\sum_{i=1}^{Q}\left[(\Phi_i - \Phi X_i)/0.5(\Phi_i + \Phi X_i)\right]^2}\right\} \end{array}\right.$ – relative form {14} or $\min F = \min\left\{\sum_{i=1}^{Q}\left|\Phi_i - \Phi X_i\right|\right\}$, or $\min\left\{\sqrt{\sum_{i=1}^{Q}(\Phi_i - \Phi X_i)^2}\right\}$ – absolute form. In other words, the vector parameter is $\underbrace{\mathbf{A}}_{(N+Q)\times 1} = \left\{\underbrace{\boldsymbol{\alpha}}_{N\times 1},\underbrace{\mathbf{\Phi X}}_{Q\times 1}\right\}$ together with its condition. The aim of using the final value of the function ΦX_i instead of the threshold $[\Phi_i]$ in the equivalent error function *F* is to find the solutions being better than those set by the threshold (if they exist).

In case, the optimal value of the function *F* approaches to zero (step {15}), this means that there might be a presence of several satisfied solutions. Here, either the threshold value $[\Phi_i]$ is possibly still broad or there is a random appearance of one solution. There are two ways to deal with this circumstance. The first one is to consider the threshold as *Q* constraints, and then acquire *Q* Pareto optimal solutions by determining the extreme of each function (steps {16} and {17}). The second one is to use condition of function F_0 minimization, which is an equivalent penalty function, in order to find the satisfied solution at the steps {18} and {19} (this technique is described in details in the Section 3.5). Among the

satisfied solutions, it needs to apply a "filter" to find the most optimal one by Pareto. Taking into account that the filtered solutions might not be the global optimal Pareto solutions, but they relieve the designer and they are the best existing solutions. If there is an available time, it is possible to verify whether they are the global optimal Pareto solutions (step {23}) by considering them as a threshold and return to the steps {13}, {14}, {15}.

Nevertheless, while dealing with this type of problem in practice, the aforementioned favorable circumstance rarely appears, and the typical circumstance is when the minimum value of the function *F* could not approach to zero. This is a case of step {20}, $\min F = E^{\circ} > \varepsilon$, it corresponds to the parameter vector $\boldsymbol{\alpha}^{\circ}$ and the final values of the function ΦX_i°. Once it is perceived that the up-to-date single-objective optimization technique is strong enough to determine min*F*, and min*F* does not approach to zero, it means that within the threshold value, indicated by the designer, there is not any satisfied solution. Here, there are three following questions:

- First, whether the threshold value of the function [Φi], which is included in the table {13}, is appropriate or not?
- If truly there no exists any satisfied solution, what to do next?
- If it needs to alter the threshold value of the function, of which one needs to do? How does it alter (increase or decrease)? And at which magnitude?

Generally speaking, the designer set the threshold value mostly based on their practical expertise, thus upon defining the solution, they themselves do not know the threshold indicated by them whether achievable. Thus, the step {20} helps them to know the thresholds indicated by them being unachievable simultaneously. After checking the deviation $\varepsilon_i = \Phi_i(\boldsymbol{\alpha}^{\circ}) - \Phi X_i^{\circ}$ among the values of the function $\Phi_i(\boldsymbol{\alpha}^{\circ})$ in comparison with the final value of the corresponding function ΦX_i° (step {21}), the designer will have two options; First, the functions $\Phi_i(\boldsymbol{\alpha}^{\circ})$ do not coincide with the preliminary observation, but they satisfy the designer, and consequently the obtained solutions $(\boldsymbol{\alpha} = \boldsymbol{\alpha}^{\circ}, \Phi_i(\boldsymbol{\alpha}^{\circ}))$ are acceptable. Or second, the designer needs to alter the threshold of the function in order to find more suitable solutions. In case it needs to alter the threshold, it will be done by using the deviation ε_i obtained at the step {21}. The negative or positive value of the deviation ε_i will decide how to alter the threshold; if it is positive, it is required to increase, and inversely to decrease. The value $|\varepsilon_i|$ decides the magnitude of alteration. If the deviation ε_i is approximately zero, the threshold of the function in relation to that of other functions is suitable and there is no need to alter. The preliminary threshold turns to be $[\Phi_i]' = [\Phi_i] + \varepsilon_i$ ({22}), and it needs to be included into the table {13} in order to repeat a calculation process again. Accordingly, when the new threshold satisfies the condition {15}, it is necessary to carry on the next steps {16} and {18} to find the satisfied and Pareto solutions. It is important to note that the alteration of threshold at step {22} is crucial; it decides whether the satisfied solution exists.

Spatial Parameter Conversion Technique

In order to avoid the difficulty of optimization algorithms, when the parameters $\underbrace{\mathbf{A}}_{(N+Q)\times 1} = \left\{ \underbrace{\boldsymbol{\alpha}}_{N\times 1}, \underbrace{\boldsymbol{\Phi X}}_{Q\times 1} \right\}$, ($i$ = 1.. Q) are set in a limited value domain, VIAM uses a spatial parameter conversion technique at the steps {1}, {5}, {7}, {10}, {14},

{16}, described in details elsewhere [14]. In Figure 4, the continuous line presents the acceptable value domain of parameter, while the dashed line illustrates the unsatisfied value domain. The spatial parameter $\boldsymbol{\alpha}$ (limited) is converted into the spatial parameter **t** (unlimited) in three cases, each of them may use a different conversion method.

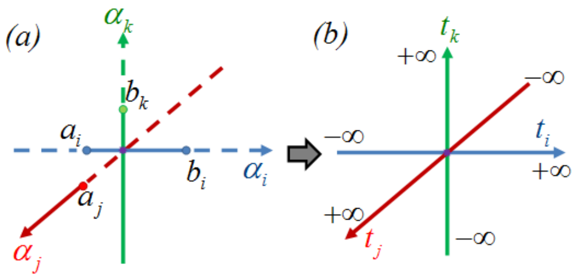


Figure 4: Spatial Parameter Conversion Technique.
(a) – Limited Spatial Parameter α; (b)- Unlimited Spatial Parameter t

After spatial conversion, the parameter vector $\underset{(N+Q)\times 1}{\underbrace{\mathbf{A}}} = \left\{\underset{N\times 1}{\underbrace{\boldsymbol{\alpha}}}, \underset{Q\times 1}{\underbrace{\mathbf{\Phi X}}}\right\}$ is referred as $\underset{(N+Q)\times 1}{\underbrace{\mathbf{T}}} = \left\{\underset{N\times 1}{\underbrace{\mathbf{t}}}, \underset{Q\times 1}{\underbrace{\mathbf{\Phi T}}}\right\}$, where $\mathbf{t} = \{t_1, t_2, \ldots, t_N\}$, $\mathbf{\Phi T} = \left\{\Phi T_1, \Phi T_2, \ldots, \Phi T_Q\right\}$. In the new space **T**, the parameter is varied from $-\infty$ to $+\infty$, hence it is not limited as before in the space **A**. This helps to improve the stability in all optimization algorithms used, because there might be any invalid solution that makes the search process stop or error occurs.

Technique by using a Penalty-Function to Determine Pareto Solutions

The penalty-function technique is a proper approach to find the solutions at the steps {18} and {19} in VIAM. Range of satisfied solutions is determined by using a condition of function F_0 (an equivalent penalty function) minimization. This function F_0 has a generalized type as $F_0(\mathbf{A}) = \sum_{i=1}^{N} Penalty(\alpha_i) + \sum_{k=1}^{K} Penalty\left(f_j(\boldsymbol{\alpha})\right) + \sum_{l=1}^{Q} Penalty\left(\dfrac{\Phi_l(\boldsymbol{\alpha}) - [\Phi_l]}{0.5 \cdot \left|\Phi_l(\boldsymbol{\alpha}) + [\Phi_l]\right|}\right)$ with a spatial parameter **A**, or $F_0(\mathbf{T}) = \sum_{i=1}^{9} Penalty\left(f_i(\mathbf{t})\right) + \sum_{j=1}^{Q} Penalty\left(\dfrac{\Phi_j(\mathbf{t}) - \left[\Phi_j\right]}{0.5 \cdot \left|\Phi_j(\mathbf{t}) + \left[\Phi_j\right]\right|}\right)$ with a spatial parameter **T**. In order to find many satisfied solutions at the step {19} with an application of single-objective optimization techniques, it is necessary to establish a sufficient small increment in search process and to use a significant number of initial test vectors [5].

It is noteworthy that the options based on the use of an equivalent error function and of an equivalent penalty-function F_0 at the step {18} are nearly similar, as they both yield the satisfied solutions. Therefore, it is possible to use flexibly one or another option based on a particular circumstance. However, the condition of an equivalent error function $\min F \le \varepsilon$ is not as strict as the one $\min F_0 = 0$. Consequently, at the step {14} if $\min F \le \varepsilon$, this is a signal, which indicates that there is a high possibility of satisfied solution existence, and the step {18} needs to be used many times with numerous initial test in order to determine potential solutions.

RESULTS AND DISCUSSIONS

Preliminary Step

Determine the maximum and minimum values of each function and include them into an interactive panel {3}.

By using a single-objective optimization method, the extreme of 9 functions can be found, and they are included

into the interactive panel Table 4 below. It is noted that the functions 3, 4, 6, 7, 8 need to be maximized. However, to facilitate the analysis, it is prone to find the minimum value of argument. Also, range of 9 functions has been determined and provided in the corresponding column of the table. Based on that, the designer set a required threshold for every function. In principal, the function would approach to the minimum value, which is presented in the upper row of the Table 4. The minimum value of the function 4 is theoretically -∞, though here with the actual calculation tool it is considered as -2.89E + 78. This means that critical speed of shaft rotation may proceed to extremely enormous.

Scenario 1 – Trend I

Based on the analysis and discussion, the designer make a decision on this particular scenario about priority order of the criteria as follows:

$$\{\Phi_1 \mapsto \Phi_6 \mapsto \Phi_5 \mapsto \Phi_9 \mapsto \Phi_3 \mapsto \Phi_4 \mapsto \Phi_7 \mapsto \Phi_8 \mapsto \Phi_2\}$$

Solution search procedure according to Scenario 1 is included in Table 5. The highlighted green color cell indicates the "good/best" obtained value of the criterion, which is being optimized deliberately. While, the highlighted red color cell implies the "bad/worst" obtained values of the rest criteria (if any). Eventually, the highlighted purple color cell represents the "relatively good / valid" obtained values, which are accepted by the experts (if any).

Table 4: Interactive Panel {3}

MINΦ_1 = 0.371	**MINΦ_2 = 0.855**	**MINΦ_3 = –124.85**	**MINΦ_4 = –2.89E+78**	**MINΦ_5 = 871.2**	**MINΦ_6 = –3000**	**MINΦ_7 = –4003.8**	**MINΦ_8 = –122700**	**MINΦ_9 = 0.0011**
…	…	…	…	…	…	…	…	…
[Φ_1]	**[Φ_2]**	**[Φ_3]**	**[Φ_4]**	**[Φ_5]**	**[Φ_6]**	**[Φ_7]**	**[Φ_8]**	**[Φ_9]**
…	…	…	…	…	…	…	…	…
MAXΦ_1 = 2.7254	**MAXΦ_2 = 1.065**	**MAXΦ_3 = –50.12**	**MAXΦ_4 = –3000.2**	**MAXΦ_5 = 2000**	**MAXΦ_6 = –2000**	**MAXΦ_7 = –997**	**MAXΦ_8 = –49996**	**MAXΦ_9 = 0.002**
Mass → min	Sawblade overall dimension → min	Argument of "First natural frequency of the saw module" → min	Argument of "Critical speed of shaft rotation" → min	Tension force magnitude → min	Argument of "Operating speed of shaft rotation" → min	Argument of "Stability of sawing processes" → min	Argument of "Initial rigidity of unstrained sawblade" → min	Sawblade thickness → min

In the Table 4, the optimal value of the function 1 is 0.371, but the designer observe that the value closest to 0.371 can be accepted being 0.5. If so, it is possible to obtain more solutions, allowing for optimizing other functions. In order to verify whether there exists the valid solution complying with the threshold $[\Phi_1] = 0.5$, it is necessary to use the minimization conditions of the error function F or $\min F = \min\{|\Phi_1 - [\Phi_1]|\} \to 0$, and one of the solutions **(S1)** is turned out, as shown in Table 5. Though the solution **(S1)** is not acceptable due to the fact that the functions 5 and 6 approach to the worst value, but the existence of several valid solutions at this step points out that the range of threshold value $[\Phi_1] = 0.5$ can be used for the next search process.

Table 5: Solution Search Procedure According to Scenario 1

Φ_1 =	i	1	2	3	4	5	6	7	8	9
0.5	α_i	0.030642	0.060499	0.001635	0.003476	0.16386	0.073975	1963.6	2116.8	–
↓	f_i	-2541.2	565.7	-18.804	1007.1	29.337	37.542	8500	723.3	2842.8
(S1)	Φ_i	0.5	0.984	-116.45	-4023.7	1963.6	-2116.8	-1223.3	-58500	0.001635
Φ_6 =	i	1	2	3	4	5	6	7	8	9
–2900	α_i	0.030656	0.060012	0.0013054	0.01849	0.2	0.11071	2000	2963.7	–
↓	f_i	-1358.7	0.3	-87.672	1239.2	5.6049	1.3817	104.	509.9	979.33
(S2)	Φ_i	0.50024	1.0563	-108.06	-4446	2000	-2963.7	-1009.9	-50104	0.0013054
Φ_5 =	i	1	2	3	4	5	6	7	8	9
1550	α_i	0.030001	0.060001	0.0016	0.000008	0.1999	0.080006	1533.9	2900	–
↓	f_i	-1481.6	-0.1	-9.3543	590.10	20.153	7.831	-4	547.5	2235
(S3)	Φ_i	0.50071	1.0550	-109.54	-4349.9	1533.9	-2900	-1047.5	-49996	0.0016
Φ_6 =	i	1	2	3	4	5	6	7	8	9
–2800	α_i	0.03001	0.06	0.0015971	0	0.2	0.07993	1550	2900	–
↓	f_i	-1491.2	0.9	-88.325	692.96	20.059	7.806	4	545.7	2228.8
(S4)	Φ_i	0.49996	1.055	-109.78	-4351.4	1550	-2900	-1045.7	-50004	0.0015971
Φ_6 =	i	1	2	3	4	5	6	7	8	9
–2760	α_i	0.030009	0.060005	0.002	0.00019	0.19947	0.036986	1543	2804	–
↓	f_i	-1952	1.1	-136.41	553	47.712	58.548	29362	1290.6	6430.6
(S5)	Φ_i	0.49991	1.054	-118.9	-4207.6	1543	-2804	-1790.6	-79362	0.002
Φ_9 =	i	1	2	3	4	5	6	7	8	9
0.0017	α_i	0.03	0.06	0.001676	0.00026	0.2	0.071454	1550	2774	–
↓	f_i	-1673.2	67.3	-91.463	666.92	24.963	12.248	5002	671.3	2771.6
(S6)	Φ_i	0.4998	1.055	-111.18	-4262	1550	-2774	-1171.3	-55002	0.001676
Φ_3 =	i	1	2	3	4	5	6	7	8	9
-111 Φ_4 =	α_i	0.03	0.06	0.0017	0.0001	0.2	0.068918	1550	2775.6	–
-4200	f_i	-1690	56.5	-94.426	659	26.242	13.373	6498	708.8	2958.7
↓ (S7)	Φ_i	0.49984	1.055	-111.65	-4248.1	1550	-2775.6	-1208.8	-56498	0.0017
Φ_7 =	i	1	2	3	4	5	6	7	8	9
-1237	α_i	0.03	0.06	0.0017002	0.00254	0.2	0.069008	1550.1	2788.4	–
↓	f_i	-1676.4	11.3	-99.054	659.03	23.951	12.799	7515	737.9	2958.5
(S8)	Φ_i	0.50006	1.055	-111.62	-4199.5	1550.1	-2788.4	-1237.9	-57515	0.0017002
	i	1	2	3	4	5	6	7	8	9
(S9)	α_i	0.03	0.060028	0.0017007	0.00244	0.19957	0.068942	1550.3	2798.3	–
	f_i	-1666.5	0.5	-99.786	659.07	23.989	12.749	7515	738	2965
	Φ_i	0.5002	1.0541	-111.62	-4198.2	1550.3	-2798.3	-1238	-57515	0.0017007

According to Trend I (step {5} in Figure 3a), the constraint $(\Phi_1 - [\Phi_1] \leq 0)$ can be added to find the smallest value for the function 6. The solution **(S2)** is obtained with the best value for the function 6 being -2963.7. For the functions 1 and 9, the affirmative values are also obtained; but this solution is useless because three functions 5-7-8 approach to the worst value. Thus, it is necessary to "slacken" or extend the condition of the function 6. While, the designer estimate that it will be a success, as soon as the operating speed of shaft rotation reaches to 2900 rpm, thus the threshold $[\Phi_6] = -2900$ is chosen. With the constraint $(\Phi_6 - [\Phi_6] \leq 0)$ and minimization condition of Φ_5, the solution **(S3)** is turned out. Here, although for the functions 1 and 6 the valid values appear (there is minΦ_5 = 1534), for the function 8 there exist the worst value being -49996, which is unacceptable. Similarly, it needs to loosen the condition and opts for $[\Phi_5] = 1550$ in order to find the extreme of Φ_9. However, the solution **(S4)** is not affirmative in comparison with the **(S3)** (Φ_8 = –50004 is very low), hence once more it is not accepted. At this point, it is notably necessary to loosen the conditions of the function 6, and after analysis the designer decide to continue the search process of valid solutions with $[\Phi_6] = -2800$. And indeed, it is rewarding at **(S5)**, when the function 8 has improved with the value of –79362, but if looking into the function 9, the value

reaches to the least of 0.002. At this time, the designer is forced to agree with the fact that the value decreases as $[\Phi_6] = -2760$ and the top limit of function 8 is not allowed to be greater than –55000. Here, there exists the solution **(S6)**, which complies with the condition of functions 1– 5 – 6 – 8. Although $\Phi_9 = 0.001676$ differentiates very much from the solution **(S2)**, it is the best one in relation to other functions. Therefore, $[\Phi_9] = 0.0017$ is opted for considering as a basis to continue finding valid solution for the function 3. In the obtained solution **(S7)**, the best value for the function 3 is –111.65, thus $[\Phi_3] = -111$ is taken into account. Still, the function Φ_4 is not optimized better than the value of –4248.1 in the solution **(S7)**. Accordingly, from here $[\Phi_4] = -4200$ is opted for finding the minimum of function Φ_7.

In the solution **(S8)**, the function 7 reaches to the optimal value of -1237.9, and other functions are also valid. Next, $[\Phi_7] = -1237$ should be used to find the minimum of Φ_8 and Φ_2, and the solution **(S9)** is turned out. Since there is a slight discrepancy between **(S8)** and **(S9)**, evidently these two solutions cannot be optimized any more with the priority order $\{\Phi_1 \mapsto \Phi_6 \mapsto \Phi_5 \mapsto \Phi_9 \mapsto \Phi_3 \mapsto \Phi_4 \mapsto \Phi_7 \mapsto \Phi_8 \mapsto \Phi_2\}$, which has been set by the designer initially. Hence, $[\Phi_8] = -57515$ and $[\Phi_2] = -1.054$ are those two optimal solutions in accordance with scenario 1. It can be seen visually in Figure 5 that value domain of parameter $\alpha_1 \div \alpha_7$ for the scenario 1 is "narrow" circumstance, it is almost a single value: $\alpha_1 = 0.03$; $\alpha_2 = 0.06$; $\alpha_3 = 0.0017$; $\alpha_4 \approx 0.00249$; $\alpha_5 = 0.2$; $\alpha_6 = 0.069$; $\alpha_7 = 1550.2$; only in case of parameter α_8 there is a range of values [2788.4; 2798.3].

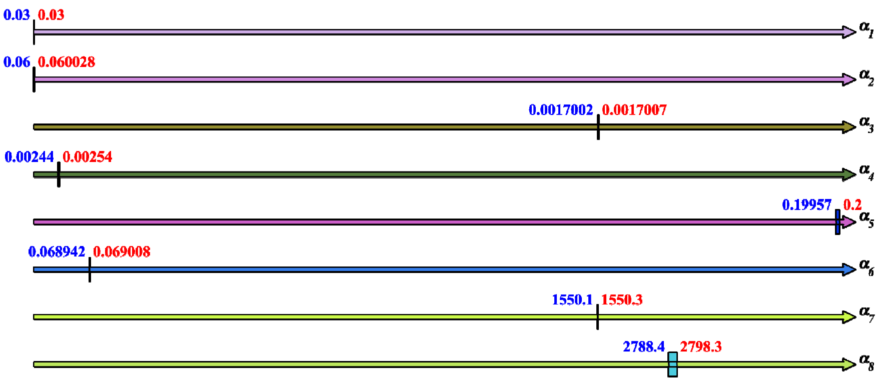


Figure 5: Intuitive Chart of Solution Distribution in Accordance with Parameters – Scenario 1

Scenario 2 – Trend II (Figure 3b)

During another manufacturing circumstance, the designer prioritize the improvement of 4 functions at the same time such as $\{\Phi_1 \& \Phi_5 \& \Phi_6 \& \Phi_9\}$. These functions have a similar importance; for the remaining five functions a random value can be obtained. Based on experience, the designer set the admissible threshold values for the four functions in table {13} as follows: $[\Phi_1] = 0.8$; $[\Phi_5] = 1000$; $[\Phi_6] = -2800$; $[\Phi_9] = 0.00147$. Here, it needs to add to the constraint 4 extra-conditions MINΦi ≤ ΦXi ≤ [Φi], where i = {1, 5, 6, 9} and check the extreme condition for the equivalent error function as $\min F = \min\left\{\sqrt{\sum_{i=1,5,6,9}\left[(\Phi_i - \Phi X_i)/0.5(\Phi_i + \Phi X_i)\right]^2}\right\} \le \varepsilon = 10^{-\mu}$. While, there exists the solution complying with this condition, this means that there might be more valid solutions. In order to find the satisfied solution, it needs to use the condition

Global $\min F_0 = 0$ together with the equivalent penalty function $F_0(\mathbf{T}) = \sum_{i=1}^{9} Penalty\left(f_i(\mathbf{t})\right) + \sum_{j=1,5,6,9} Penalty\left(\frac{\Phi_j(\mathbf{t}) - [\Phi_j]}{0.5 \cdot \left|\Phi_j(\mathbf{t}) + [\Phi_j]\right|}\right)$. From this, after filtration there are 12 Pareto optimal solutions, which are included in Table 6. These solutions are represented visually by the chart in Figure 6a. The functions are converted into a relative form (unitless) $\Phi_i^{S_j} \mapsto \frac{\Phi_i^{S_j} - \text{MIN}\Phi_i}{\text{MAX}\Phi_i - \text{MIN}\Phi_i}$, i = 1..9, j = 10..21, that they have the same scale in the chart. It shows that there is a similarity on magnitude from the functions 1, 2, 3, 5, 6, 7, 8, 9.

Table 6: Pareto Optimal Solutions in Scenario 2

NO	i	1	2	3	4	5	6	7	8	9
(S10)	α_i	0.030008	0.07868	0.00147	0.07537	0.19822	0.19475	871.24	3000	–
	Φ_i	**0.8**	1.0515	-75.763	-4854.1	**871.24**	**-3000**	-1432.2	-50033	**0.00147**
(S11)	α_i	0.033209	0.07445	0.0014622	0.07512	0.19941	0.19796	968.57	2814.5	–
	Φ_i	**0.78772**	1.0602	-70.578	-5112.7	**968.57**	**-2814.5**	-1426.7	-50102	**0.0014622**
(S12)	α_i	0.030152	0.066552	0.001469	0.070721	0.1993	0.19976	907.44	2983.9	–
	Φ_i	**0.74672**	1.0539	-75.251	-2.89E78	**907.44**	**-2983.9**	-1315	-50071	**0.001469**
(S13)	α_i	0.03	0.06258	0.001468	0.060869	0.19569	0.18433	981.89	2801.8	–
	Φ_i	**0.6947**	1.0464	-79.108	-2.89E78	**981.89**	**-2801.8**	-1257.2	-50236	**0.001468**
(S14)	α_i	0.03	0.06	0.001468	0.059957	0.19975	0.15397	989.69	3000	–
	Φ_i	**0.62054**	1.0545	-79.15	-5478.1	**989.69**	**-3000**	-1231.3	-50042	**0.001468**
(S15)	α_i	0.032574	0.065882	0.0014563	0.07112	0.2	0.18723	994.6	2800.8	–
	Φ_i	**0.71882**	1.0602	-70.038	-2.89E78	**994.6**	**-2800.8**	-1338.7	-50098	**0.0014563**
(S16)	α_i	0.030409	0.064067	0.0014598	0.06573	0.2	0.1652	968.21	2999.9	–
	Φ_i	**0.66291**	1.0558	-75.668	-5387.4	**968.21**	**-2999.9**	-1284.7	-50140	**0.0014598**
(S17)	α_i	0.031466	0.074149	0.001469	0.07999	0.1901	0.19659	938.46	2806.2	–
	Φ_i	**0.78224**	1.0381	-70.468	-4443	**938.46**	**-2806.2**	-1461.6	-51793	**0.001469**
(S18)	α_i	0.031049	0.064156	0.0014517	0.07102	0.17356	0.21831	976.8	2823	–
	Φ_i	**0.76868**	1.0042	-70.697	-2.89E78	**976.8**	**-2823**	-1316	-50376	**0.0014517**
(S19)	α_i	0.034431	0.075785	0.0014698	0.07342	0.2	0.19791	997.78	2801.5	–
	Φ_i	**0.79884**	1.0639	-70.939	-4599.9	**997.78**	**-2801.5**	-1447.7	-50018	**0.0014698**
(S20)	α_i	0.030021	0.060413	0.0014528	0.06572	0.12284	0.24242	985.9	2870.5	–
	Φ_i	**0.79635**	0.90072	-74.039	-4545.8	**985.9**	**-2870.5**	-1257.9	-50216	**0.0014528**
(S21)	α_i	0.030069	0.067572	0.0014668	0.08	0.2	0.16641	859.01	2840.7	–
	Φ_i	**0.68469**	1.0551	-71.323	-4403.5	**859.01**	**-2840.7**	-1348.5	-50129	**0.0014668**

Regarding the function 4, only 4 solutions **(S12)**, **(S13)**, **(S15)**, **(S18)** are superior to those from the other 8 functions. Thus, it indicates that to meet the condition of scenario 2, four solutions **(S12)**, **(S13)**, **(S15)**, **(S18)** are available. Similarly, Figure 6b represents valid solution distribution in accordance with parameters in scenario 2. It can be observed that the parameter domain of valid solutions in scenario 2 is quite large, which helps to find more solutions but the magnitude of function is not much different from 12 abovementioned solutions.

Scenario 3 – Trend II

Assumed that the designer could not know priority order among functions, yet all of them are considered equally due to the own significance for the saw machine. This means that 9 functions have an equal importance grade. If so, the designer have to set threshold values for all functions, such as $[\Phi_1] = 1.1$; $[\Phi_2] = 1.0$; $[\Phi_3] = -80$; $[\Phi_4] = -5000$; $[\Phi_5] = 1300$; $[\Phi_6] = -2800$; $[\Phi_7] = -1400$; $[\Phi_8] = -55000$; $[\Phi_9] = 0.0015$. Similarly, it needs to add to the constraint 9 extra-conditions $\text{MIN}\Phi_i \le \Phi X_i \le [\Phi_i]$, where $i = 1 \div 9$, then use the extreme condition for the equivalent error function

as $\min F = \min\left\{\sqrt{\sum_{i=1}^{9}\left[\left(\Phi_i - \Phi X_i\right)/0.5\left(\Phi_i + \Phi X_i\right)\right]^2}\right\} \le \varepsilon = 10^{-\mu}$ to check the existence of valid solutions. In order to find the solution, it has to use the minimization condition of the equivalent penalty-function equal to zero or $\text{Global}\min F_0 = 0$ together with $F_0(\mathbf{T}) = \sum_{i=1}^{9} Penalty\left(f_i(\mathbf{t})\right) + \sum_{j=1,5,6,9} Penalty\left(\frac{\Phi_j(\mathbf{t}) - [\Phi_j]}{0.5\cdot\left|\Phi_j(\mathbf{t}) + [\Phi_j]\right|}\right)$. From this, after filtration there are 14 Pareto optimal solutions, which are included in Table 7. In this scenario, the solutions are also represented visually by the chart in Figure 7a. The functions are converted into a relative form (unitless) $\Phi_i^{S_j} \mapsto \frac{\Phi_i^{S_j} - \text{MIN}\Phi_i}{\text{MAX}\Phi_i - \text{MIN}\Phi_i}$, i = 1..9, j = 22..35, that they have the same scale in the chart. It shows that there is a similarity on magnitude among the functions 1, 2, 3, 5, 6, 7, 8, 9. Regarding the function 4, 3 solutions **(S24)**, **(S27)** và **(S33)** are superior to the rest 11 solutions from the other 8 functions. Therefore, it points out that in order to meet conditions in scenario 3, it needs to opt for the solutions **(S24)**, **(S27)** or **(S33)**. The valid parameter domain in scenario 3, as shown in Figure 7b, is generally quite large, only for the third parameter the domain is rather narrow.

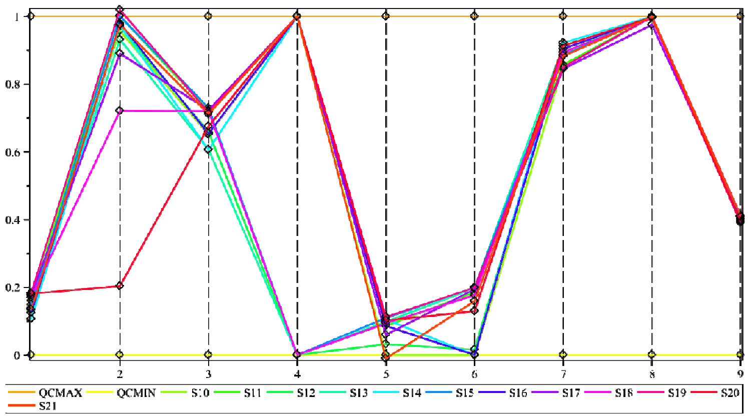


Figure 6a: Intuitive Chart of Distribution of 12 Pareto Solutions with 9 Criteria of Saw Machine in Scenario 2

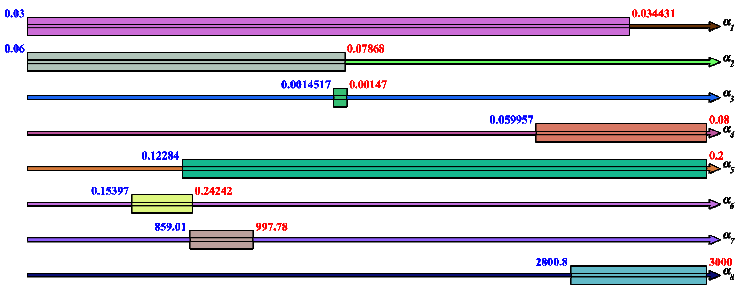


Figure 6b: Intuitive Chart of Solution Distribution in Accordance with Parameters – Scenario 2

Table 7: Pareto Optimal Solutions in Scenario 3

NO	*i*	1	2	3	4	5	6	7	8	9
(S22)	α_i	0.03	0.092196	0.0014795	0.06162	0.17129	0.29632	1271.7	2995.6	–
	Φ_i	**1.0767**	**0.99758**	**-80.403**	**-8608.4**	**1271.7**	**-2995.6**	**-1737.4**	**-55427**	**0.0014795**
(S23)	α_i	0.034333	0.065424	0.0015012	0.05336	0.16591	0.22663	1296.5	2848.4	–
	Φ_i	**0.80846**	**0.99549**	**-80.647**	**-7777.5**	**1296.5**	**-2848.4**	**-1418.2**	**-55089**	**0.0015012**

(S24)	α_i	0.033714	0.076008	0.0014981	0.05627	0.16574	0.28538	1278.1	3000	–
	Φ_i	**0.98148**	**0.99391**	**-80.144**	**-2.89E78**	**1278.1**	**-3000**	**-1536.2**	**-55027**	**0.0014981**
(S25)	α_i	0.034056	0.068089	0.0014996	0.0544	0.1573	0.23564	1290.5	2988.1	–
	Φ_i	**0.84012**	**0.97771**	**-80.382**	**-5607.3**	**1290.5**	**-2988.1**	**-1450.4**	**-55278**	**0.0014996**
(S26)	α_i	0.033063	0.068089	0.0014998	0.0544	0.1573	0.23564	1290.5	2988.1	–
	Φ_i	**0.83858**	**0.97573**	**-81.205**	**-5877**	**1290.5**	**-2988.1**	**-1458.9**	**-56064**	**0.0014998**
(S27)	α_i	0.032883	0.079165	0.0014975	0.05813	0.1507	0.31068	1267.9	2861.7	–
	Φ_i	**1.0474**	**0.96217**	**-80.046**	**-2.89E78**	**1267.9**	**-2861.7**	**-1584.1**	**-55498**	**0.0014975**
(S28)	α_i	0.03	0.089586	0.001497	0.06053	0.14733	0.29889	1195.4	3000	–
	Φ_i	**1.0737**	**0.94966**	**-82.014**	**-5092.2**	**1195.4**	**-3000**	**-1687**	**-55024**	**0.001497**
(S29)	α_i	0.031363	0.06151	0.001494	0.05499	0.11795	0.27034	1294	2870.6	–
	Φ_i	**0.86878**	**0.89363**	**-80.693**	**-5036.8**	**1294**	**-2870.6**	**-1409.6**	**-57498**	**0.001494**
(S30)	α_i	0.031312	0.074474	0.0014887	0.05695	0.15672	0.26807	1292.4	2998	–
	Φ_i	**0.93188**	**0.97106**	**-80.943**	**-31294**	**1292.4**	**-2998**	**-1544.5**	**-57129**	**0.0014887**
(S31)	α_i	0.030679	0.076114	0.0015002	0.06036	0.1403	0.30555	1145.2	2822.8	–
	Φ_i	**1.0176**	**0.93696**	**-81.298**	**-9060.3**	**1145.2**	**-2822.8**	**-1524.9**	**-55329**	**0.0015002**
(S32)	α_i	0.030001	0.078932	0.0014938	0.05974	0.17046	0.24249	1193.3	2907.8	–
	Φ_i	**0.90344**	**0.99592**	**-81.744**	**-5981**	**1193.3**	**-2907.8**	**-1572.6**	**-56244**	**0.0014938**
(S33)	α_i	0.032417	0.079009	0.0014832	0.05606	0.14229	0.33038	1298.2	2806.4	–
	Φ_i	**1.0811**	**0.94441**	**-80.486**	**-2.89E78**	**1298.2**	**-2806.4**	**-1562.1**	**-55258**	**0.0014832**
(S34)	α_i	0.033288	0.082257	0.0014999	0.05804	0.16687	0.28465	1290.4	2801.4	–
	Φ_i	**1.0135**	**0.99532**	**-80**	**-18022**	**1290.4**	**-2801.4**	**-1625.7**	**-55362**	**0.0014999**
(S35)	α_i	0.030766	0.073734	0.0014971	0.06027	0.17029	0.30496	1256.2	2872.9	–
	Φ_i	**1.003**	**0.99711**	**-80.144**	**-5127.6**	**1256.2**	**-2872.9**	**-1565.8**	**-58113**	**0.0014971**

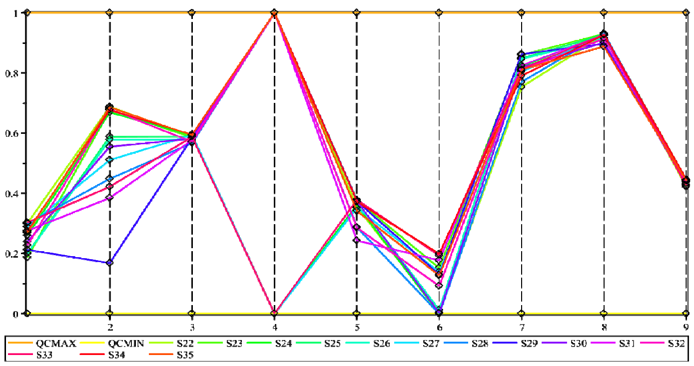


Figure 7a: Intuitive Chart of Distribution of 14 Pareto Solutions with 9 criteria of Saw Machine in Scenario 3

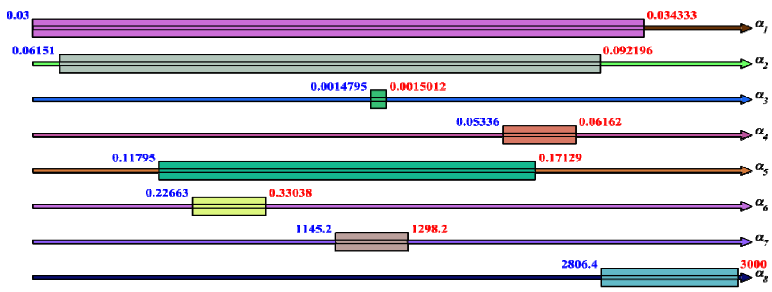


Figure 7b: Intuitive Chart of Solution Distribution in Accordance with Parameters – Scenario 3

Finally, there are 9 Pareto solutions available such as **(S8)**, **(S9)**, **(S12)**, **(S13)**, **(S15)**, **(S18)**, **(S24)**, **(S27)**, **(S33)** for all of three scenarios, as shown in Figure 8. Every solution corresponds to a particular manufacturing circumstance, defining the global behavior of the saw machine. Indeed, they are hardness, stability of saw-module, free vibration frequency, mass, geometry and technology. Based on these solutions, designer process used for the new type of frame saw machine can be carried out fluently among the stages such as detailed component design, verification of durability, hardness and stability, manufacture, installation, operation, ect. Yet, the designer can carry on opting for 3 representative solutions for three scenarios respectively in order to introduce them into manufacturing the saw machine. Those are the solutions **(S9)** – scenario 1, **(S13)** – scenario 2 and **(S27)** – scenario 3, design sketch of which is illustrated in Figure 9. Each parametric set presents a schematic diagram of the saw-module with the most important information such as sawblade dimension, part relative position, counterbalance position, etc. The designer can continue with the optimization problem of specific parts such as eccentric disks, housing parts and so on to produce the final drawing. However at these stages, the optimization design problem can be carried out easily by using the current available methods rather than VIAM, because it is mostly a single-objective optimization.

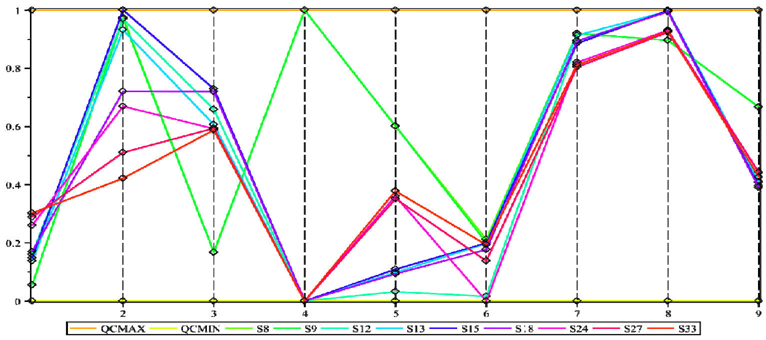


Figure 8: Intuitive Chart of Distribution of 9 Pareto Solutions with 9 Criteria of Saw Machine for all of Three Scenarios

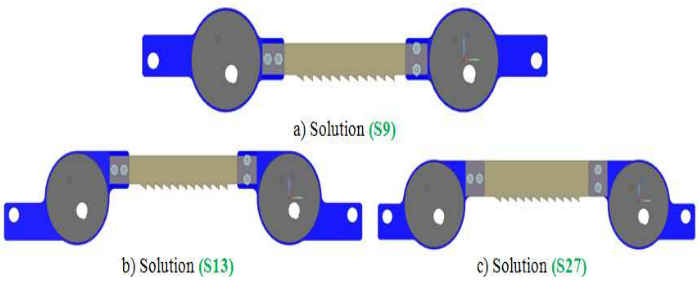


Figure 9: Illustration of Saw-Module corresponding to the Pareto Solutions

CONCLUSIONS

A multi-objective optimization problem including 8 control parameters, 9 functional constraints and 9 objective functions was elucidated properly by means of a visual interactive analysis method (VIAM) with an application of single-objective optimization techniques. Indeed, there were 28 Pareto optimal solutions, which have been determined for three manufacturing scenarios; hence the designer was able to make a suitable decision at every scenario. Also thank to VIAM, a new type of frame saw machine was designed successfully without inconsistencies among stages in design process such as concept, analysis, technology and multi-criteria decision-making processes. Besides, VIAM would definitely be reliable for designing another mechanical system apart from frame saw machine.

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